

**Examination of a Novel Method for Non-Contact, Low-Cost,
and Automated Heart-Rate Detection in Ambient Light
Using Photoplethysmographic Imaging**

by Marko Westphal

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14. ABSTRACT Non-contact measurement of physiological data, such as heart rate, respiratory rate, heart rate variability, and arterial blood oxygen saturation, provide comfortable physiological assessment without the need of wet adhesive electrodes. Consequently, in recent years, there has been an increasing interest in the investigation of such methods. One of the most promising low-cost, non-contact, and non-intrusive methods is remote photoplethysmographic imaging (iPPG). So far, different approaches and methods have been studied for this purpose. This study examined the abilities of a non-contact, webcam-based iPPG method for determining heart rate based on an algorithm inspired by recent work on Eulerian video magnification. The purpose of this work is to examine abilities and limitations, as well as the reliability of the chosen algorithm. More specifically, this study investigates the influence of varying ambient light, the distance between the measuring object and camera, as well as the influence of movements of the measuring objects on the results.					
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Contents

List of Figures	iv
List of Tables	iv
Author Biography	v
1. Introduction	1
1.1 Photoplethysmography	2
1.2 Pulse Oximetry	2
1.3 Photoplethysmographic Imaging.....	3
2. Methodology	3
2.1 Materials and Setup	4
2.2 Experimental Protocol.....	5
3. Results	6
4. Discussion	7
5. Conclusions	8
6. References	10
List of Symbols, Abbreviations, and Acronyms	12
Distribution List	13

List of Figures

Fig.1 Bland Altman plots (x -axis: difference of HR measurements between webcam and ECG method; y -axis shows differences between both methods). The right plot shows the results under no-light, distance; no-movement, and no-face-lock condition. The left plot shows the no-light, no-distance, movement, and face-lock condition.	6
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List of Tables

Table 1 Overview of the results of all 16 experiments	6
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Author Biography

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1. Introduction

In recent years, learning scientists have taken a keen interest in drawing links between affect and learning. Indeed, researchers have documented a dynamic relationship between affect and learning in which some affective states are antecedents of learning outcomes, while others are consequences of these outcomes (Guia 2013). In addition to the well-documented impact of cognition, motivation, discourse, action, and the environment on learning, the assumption that affect is inextricably bound to learning is widely supported by various studies (D’Mello 2007). For example, the four-quadrant model, which was proposed by Kort (2001), clearly links learning success or failure and affective states. During attempts for solving complicated tasks or for learning complex material, students may encounter many different emotions (i.e., affective states). They might be highly motivated by curiosity or fascination about a new topic at the beginning of their task and get puzzled or frustrated about some misconception during further processing. An affect-receptive learning system would ideally recognize these states and response to students’ emotions to increase motivation and improve learning gains.

In order to automatically identify and process affect states, such a learning system needs to be fed with appropriate affect information. Passive sensors, which capture the physical state or behavior of the learner, can be used to gather this information. The affective computing (AC) literature shows that, because of their less intrusive character, camera- or microphone-based systems are typically preferred to collect students’ emotional information. A video camera might capture facial expressions, body posture, and gestures, while a microphone might capture speech (Malatesta 2009). However, physiological signals, such as skin temperature and blood volume pulse, can be used in AC systems to identify emotions by analyzing the pattern of physiological changes. The amount of data that such signals can provide is increasing primarily due to 2 reasons: 1) the precision and data analysis techniques are improving and 2) sensors are becoming smaller and the use of wearable devices is increasing.

Usually physiological signals are recorded by equipment and techniques that are more intrusive than those recording facial and vocal expression. For example, to measure heart rate (HR) or heart rate variability (HRV), the subject typically needs to be wired up with wet adhesive electrodes on the skin and cables, which are fixed somewhere in the environment. This is often perceived as being uncomfortable and unpleasant. These conventional methods for obtaining physiological information are still essential and important for medical as well as research purposes (Liu 2012). Electrocardiographs (ECGs), which traditionally monitor the electrical activity of the heart over a period of time by electrodes attached to the surface of the skin, are used in almost every clinical environment. Pulse oximeters, which measure the blood-oxygen saturation level and pulse rate by using the light-absorbing characteristics of human blood at certain wavelengths, are commonly used during surgery. Capnographs monitor respiratory status

and pulse of patients during anesthesia and intensive care. These methods are proven and well established in the clinical field. Nevertheless, in non-clinical fields, they have some disadvantages. The main limitation in the use of these conventional methods is obviously their requirement of maintaining a direct contact with the surface of the subject's skin. This is especially a disadvantage in learning environments, where such devices may have a negative impact on the student's behavior and the learning process because they are undesirable and inconvenient. Therefore, there is an increasing interest in the development and use of non-contact methods for measuring physiological information.

One of the most promising low-cost, non-contact, and non-intrusive methods is remote photoplethysmographic imaging (iPPG). In this work, an ambient light and webcam-based iPPG method is examined for its accuracy, sensitivity, and reliability in measuring human heartbeats. The following sections provide a quick overview of the underlying technique of iPPG.

1.1 Photoplethysmography

Detection of the cardiovascular pulse wave traveling through the body is referred to as plethysmography (*plethysmos* = increase in Greek) and can be done by means such as variations in air pressure, impedance, or strain (Verkruysse et al. 2008). Photoplethysmography (PPG) is an optical measurement technique that can be used to detect blood volume changes in the microvascular bed of tissue. It has widespread clinical application, with the technology used in commercially available medical devices, for example, pulse oximeters, vascular diagnostics, and digital beat-to-beat blood pressure measurement systems (Allen 2007). PPG is based on the principle that blood absorbs light more than surrounding tissue, so a change in blood volume affects transmission or reflectance, correspondingly. The observed pulse wave, the PPG signal (blood volume pulse), is caused by the periodic pulsations of arterial blood within the peripheral vasculature and is discernible by the dynamic optical absorption that this induces in well-perfused peripheral tissue (Hayes 1998). A basic form of PPG technology requires only a few opto-electronic components: a light source to illuminate the tissue (e.g., skin) and a photodetector to measure the small variations in light intensity associated with changes in perfusion in the catchment volume (Allen 2007). A typical application of this principle is pulse oximetry.

1.2 Pulse Oximetry

A pulse oximeter monitors the blood-oxygen saturation level and pulse rate in the human blood by using the light-absorbing characteristics of oxyhemoglobin (oxygenated hemoglobin) and deoxyhemoglobin (deoxygenated hemoglobin) at certain wavelengths (i.e., 660 nm red and 940 nm infrared) and the pulsating nature of arterial blood flow. With pulse oximeters, a finger or earlobe probe is used: a red light-emitting diode (LED) and an infrared LED are located on one side of the probe, and a photodetector is located on the other side (Mengelkoch 1994). The photodetector measures the amount of red and infrared light received by the detector and calculates the amount absorbed. Oxyhemoglobin absorbs more infrared light components and

deoxyhemoglobin more red light components. The blood-oxygen saturation level can then be calculated by the comparison of the amounts of red and infrared light received. With each heart beat, there is a surge of oxygenated blood and a slight increase of the arterial blood volume. This results in more infrared light absorption during the surge and can be represented as a heartbeat (Mardirossian 1992).

1.3 Photoplethysmographic Imaging

The requirement that PPG methods must maintain direct contact with the skin of the subject limits the use of pulse oximeters in certain areas, for example, where special emphasis is placed on mobility or skin contact is inappropriate. However, this problem can be solved by using remote, non-contact pulse oximetry and iPPG methods. Such methods have been increasingly studied in recent years.

In 2007, Kenneth Humphreys and Tomas Ward presented a camera-based device capable of capturing two PPG signals at two different wavelengths simultaneously, in a remote non-contact manner. The system comprises a complementary metal-oxide semiconductor (CMOS) camera and a dual wavelength array of LEDs (760 and 880 nm). The camera was positioned and focused to an area of the volar side of the forearm close to the wrist. The experiment resulted in very accurate measurement results when measuring HR; however, it was still dependent on the use of special LEDs. In 2008, Verkruysse et al. measured remotely (>1 m) using ambient light instead of special LEDs. They used a simple consumer-level digital photo camera in movie mode and showed that PPG signals can be remotely measured on the human face without dedicated red and infrared light sources. Their results also showed that ambient light photos may be useful for medical purposes such as characterization of vascular skin lesions (e.g., port wine stains) and remote sensing of vital signs (e.g., heart and respiration rates) for triage or sports purposes. Poh et al. implemented an advanced algorithm in 2010 and showed simultaneous assessment of multiple people heartbeats with a basic laptop embedded webcam.

So far studies in this area have been involved either high-performance cameras and/or webcam-based systems. In 2012, Sun et al. examined the quality of the physiological information that could be acquired with these types of camera systems by comparing them to the data that a commercial pulse oximeter sensor can provide. The outcome of their experiments shows that the result of both the high performance camera and the webcam-based system coincide to a large extent with the results of the conventional pulse oximeter.

2. Methodology

All of the previously presented methods are based substantially on the same procedure. To monitor physiological information, a region of interest (ROI) on the forehead or wrist of the subject was recorded with a camera lens under a dedicated light source or ambient light. The

subject was asked to keep the examined ROI still to prevent possible motion artifacts. For post-experiment analysis, the video stream is then stored in an uncompressed AVI format on a personal computer (PC). Afterwards, the ROI is isolated from the video data and decomposed into the three red, green, blue (RGB) channels using the Matlab software (The Math Works Inc) and the Open Computer Vision (OpenCV) library. The color data of each channel are then spatially averaged to obtain a reference color value for each frame. For further analysis, however, only the green channel was used in previous studies. This is because there is higher green light absorption by hemoglobin than for red or blue light. It has been shown in former studies that a strong cardiac pulse signal can be isolated only from the green channel (Wim Verkruijsse, 2008). By calculating an average green value from each frame, a sample signal was determined. Followed by a fast Fourier transform (FFT) on the detected signal, a pulse signal could eventually be isolated.

In contrast to the previously presented offline post-processing methods, in this work, a fully automatic live-processing method has been applied and tested for its reliability and accuracy. For this purpose, a Python application (webcam-pulse-detector) that detects and highlights the HR of an individual in real time was used. The code for this application was developed and implemented by Tristan Hearn at National Aeronautics and Space Administration (NASA)-Glenn Research Center in support of OpenMDAO, under the Aeronautical Sciences Project in NASA's Fundamental Aeronautics Program, as well as the Crew State Monitoring Element of the Vehicle Systems Safety Technologies Project, in NASA's Aviation Safety Program (Hearn 2013). The HR detection algorithm used is inspired by the recent work on Eulerian video magnification by Wu et al. (2012) The application uses the OpenCV library to find the location of the user's face and isolate the forehead region. Through spatial decomposition, followed by temporal filtering to the frames and then amplifying the resulting signal, the flow of blood as it fills the face can be visualized and a HR can be calculated in real time.

The objective of this study is to test the used algorithm under different conditions on its robustness and accuracy compared with an ECG as a gold standard.

In addition to the assessment of the accuracy, in particular the influence of varying ambient light, the distance between the measuring object and camera, as well as the influence of movements of the measuring objects on the measurement results is investigated.

2.1 Materials and Setup

As a sensor, a simple and low-cost 2-megapixel webcam from Logitech (Logitech 2 MP HD Webcam C600) was used and connected via universal serial bus (USB) to a standard laptop computer. The default Microsoft webcam drivers were used. The camera was mounted centrally on the laptop lid and directed toward the face of the subject. The computer used was an Alienware M17x R3 with Intel® Core (TM) i7 2630QM processor with 4 GB of RAM. In the system, a Python 2.7 environment with the OpenCV library was provided for Hearn's webcam-

pulse-detector application. The source code that has been published by Hearn was only minimally modified for the purpose of logging.

As a reference system and the gold standard, an MP-150 BIOPAC data acquisition system in combination with an ECG amplifier module (ECG100C) was used. The ECG100C is a single channel, high gain, differential input, biopotential amplifier designed specifically for monitoring the heart's electrical activity. HR data were recorded, processed, and analyzed with the BIOPAC software AcqKnowledge.

Four subjects participated in this study. The subjects' demographic information is gender (3 males, 1 female), age range (28–37 years old), and race/ethnicity (Caucasian and African-Americans). The experiments were conducted indoors under relatively controlled lighting conditions. To simulate good light conditions, the blinds of the room remained opened and a large amount of daylight (1200 lx) flooded the room. Nevertheless, the illuminance of ambient light on the face of the subject varying between 800 and 1200 lx, depending on whether the sun was just obscured by a cloud or not. To simulate low-light conditions of the room, the blinds were closed. The luminous intensity of the ambient light on the subject then fell to a range between 10 and 50 lx. The illuminances were checked with a standard lux meter for measuring illuminances in workplaces before each of the respective experiments.

2.2 Experimental Protocol

Before starting the experiment, the participants were informed about the experimental setup and procedure, and wired to the ECG module. Three BIOPAC EL503 pre-gelled and medium adhesive electrodes were used to attach the wires. The electrodes were fixed in Einthoven's triangle formation to ankles and wrist (3-lead ECG). The participants were asked to sit in front of the camera and minimize the movement at the points at which the electrodes had been mounted.

Each session with the participant comprised 16 trials (or runs), and each run lasted 5 min. For each parameter combination, a particular run was performed. In this study, the impact of the 4 parameters—lighting, motion, distance, and face lock—were examined. For the lighting parameter, the room was either darkened by closing the blinds or illuminated with daylight through open blinds in combination with normal artificial fluorescent light from the ceiling. For the distance parameter, the participants were asked to position themselves either very closely to (1.5 ft) or more distantly from (3 ft) the front of the camera. For motion parameter, participants were asked to remain as still as possible or simulate a natural movement pattern in front of the screen. For the latter, the participants were asked to move their head in smooth and slow movements within a maximum angle of 45° in any direction. The requested movements included nodding and tilting the head, looking up/down and at the left/right corners of their computer screen, and making spontaneous facial expressions. With the motion parameter, the goal was to see whether the algorithm was able to balance simple and slow movements or whether these slight movements lead to inaccuracies in the measurement. The face lock parameter tested

whether a fixed focus on a specific forehead position resulted in better measurement data than the automatic face tracking option of the pulse detector application.

3. Results

A total of 16 sets of measurements were taken from each participant. The results were summarized over all participants and visualized in Bland Altman plots (Bland 1986) to graphically evaluate the average discrepancy (bias) between the webcam and ECG method. The differences between the two measurements at a given time were plotted against the average difference between the two methods. Figure 1 shows an example of 2 of the evaluated 16 plots. Table 1 also provides an overview of the results of all 16 experiments.

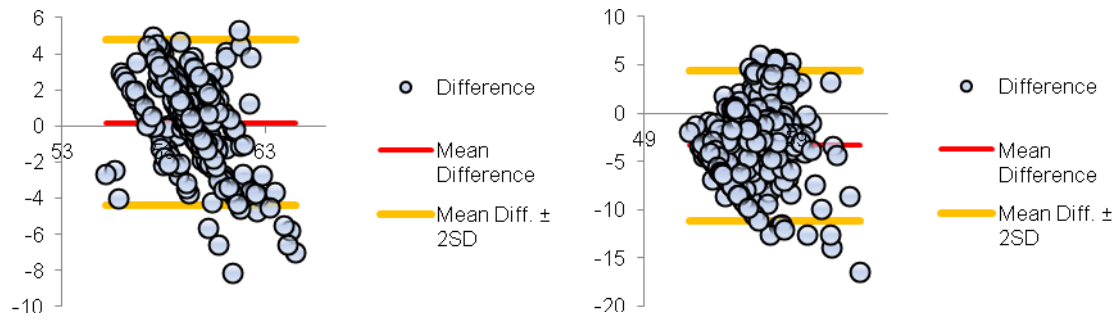


Fig.1 Bland Altman plots (x-axis: difference of HR measurements between webcam and ECG method; y-axis shows differences between both methods). The right plot shows the results under no-light, distance; no-movement, and no-face-lock condition. The left plot shows the no-light, no-distance, movement, and face-lock condition.

Table 1 Overview of the results of all 16 experiments

No.	L	D	M	FL	Mean Difference	SD	Mean Diff. + 2 SD	Mean Diff. - 2 SD
1	0	0	0	0	0.1205	2.8370	5.7946	5.5536
2	0	0	0	1	0.4557	2.5735	4.6913	5.6026
3	0	0	1	0	1.3316	7.8826	14.4336	17.0968
4	0	0	1	1	3.3564	3.8750	4.3936	11.1064
5	0	1	0	0	0.1973	2.2827	4.7627	4.3681
6	0	1	0	1	0.2418	2.2728	4.7875	4.3038
7	0	1	1	0	0.5204	8.4855	17.4914	16.4507
8	0	1	1	1	2.5915	6.3091	10.0267	15.2097
9	1	0	0	0	0.1351	2.8224	5.7799	5.5097
10	1	0	0	1	0.0766	2.7694	5.4623	5.6154
11	1	0	1	0	15.5239	9.9197	4.3155	35.3634
12	1	0	1	1	4.3981	6.4414	8.4847	17.2810
13	1	1	0	0	0.2481	3.6735	7.0990	7.5951
14	1	1	0	1	0.2211	2.9463	6.1138	5.6715
15	1	1	1	0	4.2695	7.0245	9.7794	18.3185
16	1	1	1	1	7.2056	8.9417	10.6778	25.0890

Note: L = light, D = distance, M = movement, FL = face lock; 0 = no, 1 = yes

In the left plot of Fig. 1, experiment no. 5 (see Table 1) is visualized. The conditions for runs of experiments of this kind are very low ambient lighting (no ceiling light and window blinds closed), the subject was at a distance of 3 ft from the camera, movements were avoided as far as possible, and the face lock was disabled. The mean and the standard deviation of the differences were determined and the 95% marks of agreement (± 1.96) were calculated. The plot on the left shows that, for this experiment, the measured differences of the tested method, under the given conditions in 95% of all measurements, are no larger than 4.8 bpm. The average bias is only 0.19 bpm. In contrast, the bias is 3.35 bpm for experiment no. 4 (right plot) and the deviation can be as high as 11.1 bpm. The main difference between these two experiments is the movement parameter. In experiment no. 4, (natural) movement was requested to a certain extent, whereas in experiment 5, movements were suppressed far as possible.

Table 1 provides an overview of all the runs and over all participants. It can be clearly seen that movement is the factor that most influenced the accuracy of the results. Movements by the subject during data recording always resulted in large deviations. Further details of the results are discussed in Section 4.

4. Discussion

In this study, an automatic live-processing method for non-contact, webcam-based HR detection has been applied and tested under the conditions of movement, distance, and inadequate ambient light. All these conditions have been tested with or without locking the device to focus only on the forehead area of the participants. To cover all combinations of these parameters, 16 experiments were performed and analyzed. For each permutation, participant data were recorded for a duration of 5 min. Thus, a total of 320 min of data were collected, analyzed, and visualized. The approach was to compare an established and well-proven clinical HR monitoring system with a recently implemented HR detection algorithm inspired by the work on Eulerian video magnification (Wu 2012). The results, summarized in Table 1, show that reliable results are strongly dependent on the right environmental conditions. As can be seen from Table 1, movement has the strongest influence on the measurement result. If the ROI is nearly free of movement, the discrepancy between the 2 methods is relative low. The mean bias \bar{d} in these cases was always lower than 0.46 bpm and under optimal conditions was as low as 0.076 bpm. This indicates that the 2 applied methods are systematically producing the same results.

Although, the 95% limits of agreement in these cases show that a deviation of up to 7.5 bpm is likely even under good conditions. The mean deviation under the no-movement condition is 5.57 bpm. Under in motion condition, the results are burdened with large deviations and are ambiguous; the tested algorithm mostly failed to deliver a reliable measurement when movement was present. The mean bias was always high in these cases and deviation within the limits of agreement could be as high as 30 bpm.

It can also be seen that the face-lock condition cannot improve the accuracy of the result dramatically. This probably stems from the fact that even while trying to remain motionless, small uncontrollable movements of the head always affect the measurement. While the ROI is fixed in the image, the participant moves the imaged area by uncontrolled movements. This leads to motion artifacts that influence the image analysis.

Compared with the impact of movement, varying the ambient light had only a small influence on the measurement results of this study. Neglecting those influenced by movement, we obtained an average bias \bar{d} of 0.22 bpm for the measurements in the darkened environment and $\bar{d} = 0.18$ bpm in daylight.

Hence, the results of the webcam method tend to be in agreement with the results of the ECG method. However, within the 95% limits of agreement, this study shows better results in the darkened environment (4.77 bpm) than in daylight (5.72 bpm). The same trend can also be seen even when the less-precise data in the measurement under motion of the subject are included: 5.69 bpm in daylight compared with 7.34 bpm in the darkened environment. Basically, better results would be expected in good rather than in poor light conditions. The reason for results contrary to this expectation is probably due to the special camera technology. The camera model used employs a so-called RightLight 2 technology, which automatically adjusts the exposure of the image to compensate for dim or poorly lit settings. With this technology, faces stand out from the background more clearly, so that the algorithm was able to identify and focus on the ROI faster and clearer.

5. Conclusions

The abilities of a low-cost, non-contact, webcam-based PPG imaging method for determining heart rate were investigated under various environmental conditions. It has been shown that the particular movements of the subject have a greater influence on the accuracy of the measurement results than the other parameters. However, if one used better methods for motion tracking, these inaccuracies would likely be minimized. A modification of the algorithm that implements a motion-tracking ability should be considered for future studies. If movement can be suppressed, relatively good results can be obtained with the examined method, both in daylight as well as under low-light conditions. The deviations between the reference system and webcam-based method in these cases were, on average, less than 6 bpm. Furthermore, the effect of varying ambient light was tested and was found to have no significant influence on the accuracy of the result. Nevertheless, one must consider that the camera used here automatically enhanced the exposure of the face of the subject when the ambient lighting decreases.

While, even under best conditions, the accuracy of the iPPG method is not as good as that of the reference ECG device, its non-contact, non-intrusive, and low-cost characteristics still provide a

great advantage. If a good estimation of HR data is already sufficient and the trend is more interesting than the exact value at a given time, the iPPG method could provide adequate results. Taken this into account, this method certainly would be very useful in adaptive learning environments. The affective states of the learners could be detected in a wireless manner that would not interfere with the learning process. Even though this study merely examined the measurement of heart rates, it should be kept in mind that by extending the used algorithm, parameters such as respiratory rate, HRV, and arterial blood oxygen saturation could be measured as well.

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List of Symbols, Abbreviations, and Acronyms

AC	affective computing
ARL	US Army Research Laboratory
CMOS	complementary metal-oxide semiconductor
ECG	electrocardiograph
ESEP	Engineer and Scientists Exchange Program
FFT	fast Fourier transform
HR	heart rate
HRED	Human Research and Engineering Directorate
HRV	heart rate variability
iPPG	photoplethysmographic imaging
LED	light-emitting diode
LITE	Learning in Intelligent Tutoring Environments
NASA	National Aeronautics and Space Administration
OpenCV	Open Computer Vision
PC	personal computer
PPG	photoplethysmography
RPG	red, green, blue
STTC	Simulation and Training Technology Center
USB	universal serial bus

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